Sustainable Energy Management for Microgrid Clusters Through a Two-stage Strategy Using Shared Storage and Flexible Loads

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***Abstract*— The inherent intermittence of renewable generation and variable load demands present ongoing challenges in microgrids' reliable and efficient operation. In response, stakeholders and operators have turned to clustering the geographically adjacent microgrids as a solution. In this context, this paper introduces a two-stage energy management strategy for microgrid clusters by leveraging the capability of a shared battery energy storage system (SBES) to reduce operational costs and emissions while providing a spinning reserve to eliminate load shedding. In the primary stage, the proposed approach devises optimal day-ahead operation policies, while the second stage employs a cooperative strategy to further optimize the operational efficiency of the cluster. The energy management problem is accurately formulated as a mixed integer quadratic programming (MIQP) optimization, which incorporates linear terms in the problem's constraints. The formulation accounts for operational costs associated with BESS including expenses of charging/discharging and changes in operating states (CiOS). Additionally, a sensitivity analysis of installed SBES capacity is conducted. A case study with real-world data validates the efficacy of the proposed approach, with results indicating a minimum reduction of 2% in total operational costs, contingent upon the realizable flexibility and the shared battery system capacity.**

Keywords*— *energy management, optimization, storage system, MIQP, microgrid cluster

I. Introduction

The technology of microgrids is evolving through the interconnection of multiple geographically adjacent microgrids known as microgrid clusters (MCs), aiming to improve overall system reliability and energy utilization efficiency. Microgrid clusters offer economic advantages by reducing costs for end-users, eliminating active losses, and decreasing emissions [1], [2], [3]. In scenarios where microgrids have excess energy, the concept of clustering becomes beneficial as they can collaborate with microgrids facing energy deficits by exchanging surplus energy. Various architectural configurations for microgrid clusters are explored in [4], [5], with the parallel connected microgrids alongside an external grid and the mixed parallel-series connection emerging as particularly viable options. In this dynamic landscape, the vital role of energy management systems cannot be overstated. Energy management constitutes the strategic level of microgrid control, while power management and local controls operate within the tactical level. Consequently, the selection of an adept energy management strategy emerges as a critical determinant, directly impacting the profitability of stakeholders and the satisfaction of demand-side entities.

Exploring the notion of EMS in microgrid clusters, an energy management strategy for off-grid microgrid clusters, employing tube model predictive control is proposed in [6], aiming to optimize energy scheduling with minimal economic trade-offs. However, it does not address transactions with the main grid or incorporate considerations of load demand flexibility. In reference [7], researchers have proposed an interactive model aimed at managing energy within clustered microgrids in distribution systems by introducing a multi-level optimization model to facilitate coordinated energy management across microgrids and clustered microgrids at the lower level, and between clusters and distribution systems, as well as upstream networks at the upper level. However, the study neglected to consider the potential of embedded energy storage systems shared between clusters. The research in [8] delves into devising an EMS using a multi-step hierarchical decentralized strategy for a cluster of interconnected isolated MGs neglecting embedded energy storage systems. In addition, authors in [9] employ a battery storage logistic model to introduce an EMS model for microgrid clusters. Notably, both studies focused on microgrid clusters operating independently, overlooking grid exchange capability. Upon reviewing the literature, it is evident that embedded storage systems, particularly in microgrid clusters, have been overlooked. Yet, a computationally efficient method that considers the precise mathematical formulation of energy storage systems remains unexplored. Moreover, there is limited discussion on sustainable solutions that reduce load shedding while prioritizing low carbon emissions. Therefore, this study proposes an approach wherein a cluster of microgrids invest in a shared storage system to minimize the operational cost. The main contributions of this paper can be outlined as follows:

- Proposing a two-stage energy management strategy for MCs according to the mixed-integer quadratic programming (MIQP) approach
- Embedding a shared BES to compensate for the supply deficiencies while clustered microgrids cooperate in

meeting neighbouring microgrids' demand in different time intervals.

- Formulating the cost of alteration in battery operation mode, along with the battery degradation cost due to charging or discharging and the lifespan investment cost, to avoid unexpected expenses.

II. The Methodology Framework

The current study focuses on a cluster of interconnected microgrids, each equipped with its own EMS designed to optimize the operation schedules of energy generation and consumption considering the day-ahead forecasted data. These microgrids are linked to a central community EMS, which oversees energy storage utilizing a shared battery energy storage (SBES) system. The utilization of SBES enhances the reliability and flexibility of individual microgrids. Each microgrid comprises its own BES, renewable energy generation (such as photovoltaic systems), and conventional fossil fuel-based generation units. The system can operate in either grid-connected or isolated modes, with the cluster EMS (C-EMS) orchestrating power exchanges with the grid to minimize costs and optimize overall efficiency. The load flexibility of microgrids is collectively managed among microgrids. Additionally, the minimum state of charge of battery energy storage systems (BESs) is taken into account to prevent complete depletion, which could negatively impact battery performance. Energy transactions occur between neighbouring microgrids, as well as between the C-EMS and the main grid, aiming to minimize the overall operational costs of the system while considering load flexibility and energy storage capabilities for future intervals. From the perspective of the Distribution System Operator (DSO), the C-EMS functions as a price-taker. This implies that the electricity price between the C-EMS and the DSO remains unaffected by the scheduling strategy and is determined solely by the electricity market.

III. Proposed Two-Stage Energy Management Strategy

In the proposed method, each microgrid's EMS optimizes the schedule of its associated microgrid, which is then coordinated by the C-EMS. After optimizing the system, the C-EMS facilitates transaction settlements to ensure the optimal operation of individual microgrids. Fig. 1 provides a visual representation of the proposed two-stage strategy. Notably, the transmission of load and generation data to the system operator (C-EMS) is avoided, with decisions instead based on net load/generation, which can be either negative or positive. This approach ensures the confidentiality of internal microgrid information, enhancing security measures.

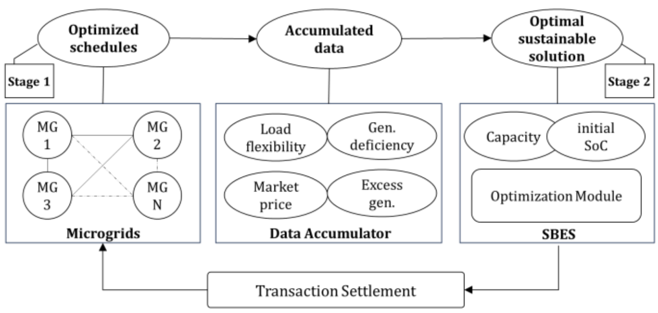

Fig. 1. The procedure of the two-stage energy management strategy

The subsequent subsections outline the details of both stage 1 and stage 2 of the procedure.

A. Stage 1: Optimized Individual EMS Scheduling

Stage 1 of the proposed strategy focuses on optimizing individual microgrids, each comprising a conventional generation unit (CGU), battery storage system (BES), and photovoltaic generation unit (PV) to meet flexible load demands. To execute this stage, the mathematical formulations are presented in (1) to (18) where the cost formulation is developed according to [10], [11], [12], [13]. The inputs for this stage include the generation capacity and specifications of the CGU, PV, and BES, along with the initial state of charge (SoC) of the BESs. Additionally, the individual EMSs should be supplied with forecasted market prices for electricity, irradiance, and load demand. The optimization process of stage 1 yields the day-ahead hourly generation schedule and SoC of the BESs as outputs. The objective function orchestrating the optimization of operational strategies to minimize expenditure while ensuring a reliable power supply is formulated in (1). It integrates factors including exchange-related expenses, generation costs, and BES operational costs to achieve optimal economic performance. As elucidated in (4), the cost of energy exchange for Microgrid m can be computed as the disparity between the energy imported/exported by the EMS either from/to internal or external sources of the cluster. It is imperative to underscore that at this stage of the energy management strategy, the optimal operation of the microgrid is determined by considering the total exchanges, with the subsequent stage accounting for the eventual optimal energy exchange with the main grid. Moreover, changes in BESs' operating state can be calculated by (6).

OF-I:

$$\min\begin{pmatrix} Cost^{CGU}+Cost^{RES}+Cost^{exchange} \\ +Cost^{BES,ch/dch} \end{pmatrix}\forall_{m\in MG} \tag{1}$$

$$Cost^{CGU}=\sum_{i=1}^{CGU}\sum_{h=1}^{H}a_i^{CGU}(\mathrm{E}_{i,h}^{CGU})^2+b_i^{CGU}(\mathrm{E}_{i,h}^{CGU})+c_i^{CGU} \tag{2}$$

$$Cost^{RES}=Cost^{PV}=\sum_{k=1}^{K}\sum_{h=1}^{H}\sigma_k.E_{k,h}^{PV} \tag{3}$$

$$Cost_m^{exchange}=\sum_{h=1}^{H}\left(\lambda_{m,h}^{imp}E_{m,h}^{imp}\varphi_{m,h}^{imp}-\lambda_{m,h}^{exp}E_{m,h}^{exp}\varphi_{m,h}^{exp}\right) \tag{4}$$

$$Cost_j^{BES,ch/dch}=\sum_{h=1}^{H}\left(\alpha_j^{BES}(\mathrm{E}_{j,h}^{BES})^2+\beta_j^{BES}\right) \tag{5}$$

$$Cost_j^{BES,\mathrm{OS}}=\rho_j.\left(\sum_{h=0}^{H-1}\left(\tanh(\xi[\tanh(\xi E_{j,h}^{BES})-\tanh(\xi E_{j,h-1}^{BES})])\right)\right) \tag{6}$$

In the above formulas, i, k, j, h, and m are the indices representing generation units, BESs, individual microgrids, and hours of the day, respectively. Also, E represents the electricity flowing through various components or imported/exported by individual EMSs. The parameters α,β,σ, and ρ are constant coefficients. φ^{imp} and φ^{exp} are the electricity prices for importing and exporting. In the developed model in this paper, the following parameters are the decision variables:

$$\lambda_{m,h}^{imp},E_{m,h}^{imp},\lambda_{m,h}^{exp},E_{m,h}^{exp},E_{i,h}^{CGU},E_{i,h}^{CGU},E_{j,h}^{BES},\gamma_h^{ch},\gamma_h^{dch},E_{k,h}^{PV}$$

The mathematical model of a BES within a microgrid EMS encompasses various factors to effectively capture its behaviour and impact on energy optimization. Typically, this model, formulated in (5), (6), and (15), incorporates elements such as the battery's SoC, charging and discharging rates, efficiency, and capacity constraints. Constraints on the battery's capacity, charge/discharge rates, and maximum/minimum state of charge further shape its operational behaviour within the microgrid EMS. Additionally, factors like aging effects resulting from continuous alteration in the operating state escalating the BES degradation are integrated into the model to enhance its accuracy and reliability. The constant coefficients are set in a way that considers the cost of capacity fading. The cost associated with not utilizing the battery system during periods of zero charging or discharging, is computed by the intercept of β_j^{BES}. Moreover, the changes in the operating state (CiOS) incur an associated cost, which is computed by (6).

The above objective function adapts to fluctuating energy demands, renewable energy availability, and market prices, orchestrating efficient utilization of resources while meeting operational constraints. The most important constraint that is referred to as a hard constraint is the power balance between generations and consumption within the whole network considering the energy exchanges with the grid as presented in (16). The operation of CGUs in the optimization model should satisfy the constraints (7), and (8) which relate to minimum and maximum generation capacity, and ramp rate limits (represented by *R)*, respectively. It is worth mentioning that when the CGU operates continuously at least at the minimum generation level of $P_{i,min}^{CGU}$, the need to consider shutdown or startup costs is eliminated. BES operation is also subject to constraints (12) to (15), showing the output rate limits, avoiding charging/discharging at the same time, and the boundaries of batteries' SoC which are to increase the lifetime and to decrease aging, respectively. It should be noted that positive values indicate discharging, while negative values indicate charging, as the BES is regarded as an energy source rather than a demand. Furthermore, to avoid the greedy action of EMS to import the electricity at a time step and make a profit by exporting it at the immediate next time step (17) is applied.

$$P_{i,\min}^{CGU} \le E_{i,h}^{CGU} \le P_{i,\max}^{CGU} \tag{7}$$

$$E_{i,\mathrm{h}-1}^{CGU} - R_i^{CGU} \le E_{i,\mathrm{h}}^{CGU} \le E_{i,\mathrm{h}-1}^{CGU} + R_i^{CGU} \tag{8}$$

$$P_{total,\min}^{PV} \le \sum_{k=1}^{PV}\sum_{h=1}^{H} E_{k,h}^{PV} \tag{9}$$

$$\lambda_{m,h}^{imp} \cdot E_{m,h}^{imp} \le P_{\mathrm{m,max}}^{imp} \tag{10}$$

$$\lambda_{m,h}^{exp} \cdot E_{m,h}^{exp} \le P_{\mathrm{m,max}}^{exp} \tag{11}$$

$$P_{j,\max}^{BES,ch} \le E_{j,h}^{BES} \le P_{j,\max}^{BES,\mathrm{d}ch} \tag{12}$$

$$\gamma_h^{ch} + \gamma_h^{dch} = 1 \tag{13}$$

$$SoC_{\mathrm{j,min}} \le SoC_{\mathrm{j},h} \le SoC_{\mathrm{j,max}} \tag{14}$$

$$SoC_h = SoC_{h-1} + \eta_{\mathrm{j},ch}^{BES}(\gamma_h^{ch}\frac{E_{j,h}^{BES}}{Cap_j^{BES}}) - \frac{1}{\eta_{\mathrm{j},dch}^{BES}}(\gamma_h^{dch}\frac{E_{j,h}^{BES}}{Cap_j^{BES}}) \tag{15}$$

$$\left(E_h^{Load} + \gamma_h^{ch}\sum_{j=1}^{BES} E_{j,h}^{BES,ch} + \lambda_{m,h}^{exp}\cdot E_{m,h}^{exp}\right) = \left(\lambda_{m,h}^{imp}\cdot E_{m,h}^{imp} + \gamma_h^{dch}\sum_{j=1}^{BES} E_{j,h}^{BES,dch} + \sum_{k=1}^{PV} E_{k,h}^{PV} + \sum_{i=1}^{CGU} E_{i,h}^{CGU}\right) \tag{16}$$

$$\varphi_{m,h}^{exp} \le \varphi_{m,h}^{imp}\ \forall\, m \in M \tag{17}$$

$$\lambda_{m,h}^{imp} + \lambda_{m,h}^{exp} = 1 \forall\, m \in M \tag{18}$$

Where P_{max} and P_{max} denote the maximum and minimum power rates. The BESs charging and discharging efficiency are denoted by η_{ch} and η_{dch}, respectively. Here, *SoC* stands for the state of charge of BESs and *Cap* denotes their capacity. It is worth noting that:

$$\lambda_{m,h}^{imp}, \gamma_{j,h}^{dch}, \gamma_{j,h}^{ch}, \lambda_{m,h}^{exp} \in \{0,1\}\ \forall\left(m \in M,\, j \in J\right) \tag{19}$$

B. Stage 2: Optimized C-EMS Scheduling

a) Sustainable decision-making: After optimizing all individual microgrids, the second stage of the energy management strategy focuses on optimizing the entire system sustainably. The centralized C-EMS achieves economic optimization by favouring the use of local renewable-based sources to meet total demand, minimizing the need for grid purchases or conventional generation units to reduce CO2 emissions. Moreover, in terms of customer welfare, C-EMS solutions prioritize supplying all demand, even if it means purchasing from the grid, to ensure efficient, environmentally friendly, and reliable solutions for daily operating strategies of SBES and transactions within the system and with the grid. Additionally, load shedding is adjusted to match the maximum load flexibility, encompassing non-critical loads thereby ensuring high customer satisfaction. Fig. 2 provides the flowchart of the proposed energy management strategy.

b) Optimization Problem Formulation: This phase of optimization yields the optimal solution for the entire MC. The formulation of the system to be optimized differs slightly from that of Stage 1. The objective function formulation previously formulated, needs updating, as this stage of the proposed strategy does not account for any generation from the community, unlike for individual microgrids. In the second stage of optimization shown by (20), the same mathematical formulation for storage systems, as detailed in Section III.A, is utilized with slight variations. In addition to factoring in the degradation cost, it is essential to consider the cost associated with CiOS and the investment cost of installing SBES beyond OF-II. Given that large batteries typically utilize lead-acid technology [14], (21) computes the daily life cost of SBES, with ϕ representing the annual cost of SBES per unit capacity. In a manner akin to stage 1, the grid transactions of C-EMS are described through the hourly power exchange rate, incorporating buying and selling prices with the aid of binary variables to activate or deactivate the grid exchange. In this context, the constraints stated in the previous section are applied here as well with slight revision, particularly, the power balance constraint formulated in (22) to (24).

OF-II:

$$\min\left(Cost_{S-EMS}^{exchange} + Cost_{ch/dch}^{SBES}\right) \tag{20}$$

$$Cost_{life}^{SBES} = \phi.(\frac{Cap_{\max}^{SBES}}{365}) \tag{21}$$

$$\left(L_h^{SEMS} + \gamma_h^{ch}.E_h^{SBES,ch} + \lambda_h^{buy} \cdot E_h^{buy}\right) \tag{22}$$
$$= \left(\lambda_h^{sell} \cdot E_h^{sell} + \gamma_h^{dch}.E_{j,h}^{SBES,dch} + G_h^{SEMS}\right)$$

$$SoC_{\min}^{SBES} = \alpha_{\min}^{SBES}.Cap_{\max}^{SBES} \tag{23}$$

$$SoC_{\max}^{SBES} = \beta_{\max}^{SBES}.Cap_{\max}^{SBES} \tag{24}$$

Where L and G represent the net load demand and generation as observed by S-EMS. In the second stage, the generation deficiencies of microgrids and their available excess generations serve as the demand and source for C-EMS. Equations (25) and (26) delineate how to calculate these parameters based on the optimal operational schedules of microgrids.

$$\boldsymbol{D} = \boldsymbol{G} - \boldsymbol{L} \tag{25}$$

$$\begin{bmatrix} d_{1,1} & \cdots & d_{1,h} \\ \vdots & \ddots & \vdots \\ d_{m,1} & \cdots & d_{m,h} \end{bmatrix} = \begin{bmatrix} g_{1,1} & \cdots & g_{1,h} \\ \vdots & \ddots & \vdots \\ g_{m,1} & \cdots & g_{m,h} \end{bmatrix} - \begin{bmatrix} l_{1,1} & \cdots & l_{1,h} \\ \vdots & \ddots & \vdots \\ l_{m,1} & \cdots & l_{m,h} \end{bmatrix} \tag{26}$$

Let x_h equal to $\sum_{m=1}^{MG} D_{m,h}\ \forall_h$ then:

$$G_h^{SBES} = \begin{cases} |x_h| & if\ x < 0 \\ 0 & otherwise \end{cases} \tag{27}$$

$$L_h^{SBES} = \begin{cases} x_h & if\ x > 0 \\ 0 & otherwise \end{cases} \tag{28}$$

The integration of SBES aims to mitigate fluctuations in renewable energy generation and enhance system reliability. Despite the efforts of energy management systems to find optimal solutions, there remains a risk of some loads going unsupplied due to inaccuracies in load demand and renewable generation forecasts. To mitigate this risk, a spinning reserve is essential, ensuring adequate backup power is available to meet unexpected demand fluctuations. Therefore, the objective at this level shifts towards achieving sustainable solutions, wherein the minimum spinning reserve is factored in. This reserve constitutes the unused portion of the SBES or the residual SoC limit. The determination of this reserve amount is contingent upon the forecast accuracy of historical data, guaranteeing sufficient backup capacity. Moreover, by transmitting only aggregated information, the proposed strategy effectively reduces the exposure of sensitive data to potential cyber threats and minimizes the risk of disclosing operational details.

IV. Solving the Optimization Problem

Researchers present and employ promising techniques for solving energy management optimization problems and tackling related challenges in microgrid applications either a single microgrid or a system of interconnected microgrids. Proposed algorithms include neural networks and machine learning-based methods [15], [16], [17], mathematical approaches like linear and non-linear programming [17], [18], solutions based on game theory [16], [19], and multi-agent systems [18], [20]. However, there are limitations and challenges, such as reliability and avoiding local minima traps, search capabilities, handling of convergences, customization and dimensional settings, and efficiency, especially in managing energy storage operations. Keeping this information in mind, the authors are motivated to propose precise mathematical formulation and employ the MIQP approach with quadratic terms in the objective function and linear terms in the constraints to precisely determine the optimal solution for scheduling generation and exchanges, rather than relying on estimations from non-exact methods. If the nonlinear terms are converted into linear forms, the problem can be reformulated as mixed-integer linear programming, albeit with some linear approximations. Given sufficient computational resources in terms of speed and memory, solving the nonlinear problem directly can provide greater accuracy, even though it may be computationally more intensive. In this paper, the MIQP optimization problem is solved using a free license of Gurobi™ optimizer in the Python environment to find the day-ahead optimal schedule of the cluster.

V. Results and Discussion

To assess the effectiveness of the proposed two-stage strategy, several analyses are conducted in this section using real data from a cluster of three microgrids, along with price data obtained from the Australian energy market for the NSW state. Furthermore, the sensitivity analysis of the SBES capacity and characteristics is presented. Each microgrid within the cluster features identical components, including a renewable generation source, a battery storage system, and a CGU. Additionally, each MG is equipped with a central EMS to optimize its operation over a day-ahead timeframe divided into 24 timeslots. Initial parameter values are provided in Table (1) for reference. For simplicity, uniform characteristics for the components across all microgrids are assumed.

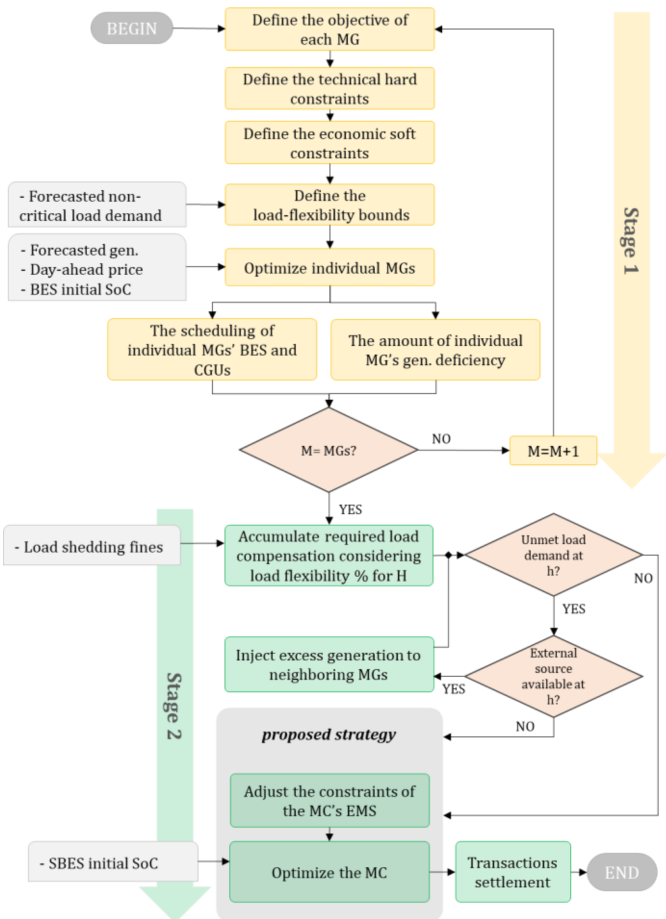

Fig. 2. The flowchart of the two-stage energy management strategy for a microgrid cluster

Figures 3 and 4 illustrate the unsupplied demand of microgrids and their available excess generation. EMS endeavours to minimize the operational cost of individual microgrids by optimizing the orchestration of BESs charging and discharging, as well as importing or exporting electricity, taking into account load demand flexibility. Consequently, there are instances where generated power is available for export, while at other intervals, power must be imported to meet uninterruptible demand. Figure 5 depicts the CiOS of each microgrid's BES along with their power profile. CiOS increases by one whenever the BES's power injection or withdrawal profile intersects the zero line. Consequently, as long as the profile remains above or below the zero line, the CiOS does not contribute to BES's costs. Therefore, changes in the amount of power do not affect CiOS; while influencing the degradation cost.

The operational cost of microgrids in individual operation mode is computed using the formulation detailed in section III. The day-ahead costs for microgrids 1, 2, and 3 are determined to be $230.62, $368.23, and $438.97, respectively. Notably, the operational cost demonstrates a proportional relationship with the load demand levels of each microgrid, as illustrated.

TABLE 1. COMPONENT'S INPUT PARAMETERS

Parameter	*Value*
$a_i^{CGU}, b_i^{CGU}, c_i^{CGU}$	*0.00132, 0.05, 2.5*
R_m^{CGU} , Cap_m^{CGU}	*R=[10,20,20], Cap=[40,50,70]*
Cap_m^{BES}	*71, 28.4, 56.8*
$\alpha_j^{BES}, \beta_j^{BES}$	*0.00108, 0.5*
$\alpha_{j,\min}^{BES}$	*0.05*
$\beta_{j,\max}^{BES}$	*1*
ξ	*10*
ρ_j	*0.3*
$P_{k,\max}^{PV}$	*51, 27.5, 62*
σ_k	*0.005*

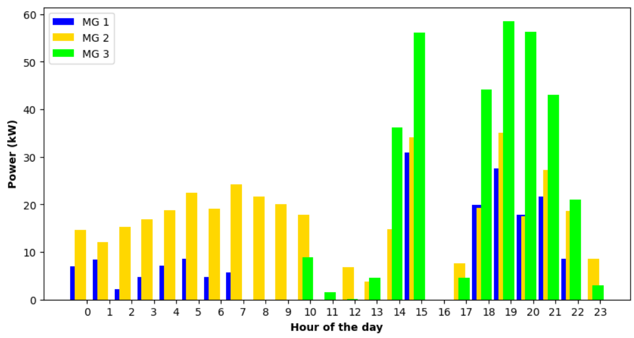

Fig. 3. Required power to be imported by each microgrid

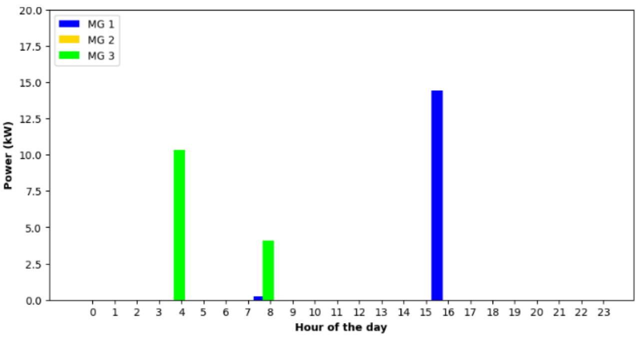

Fig. 4. Available excess generation of each microgrid

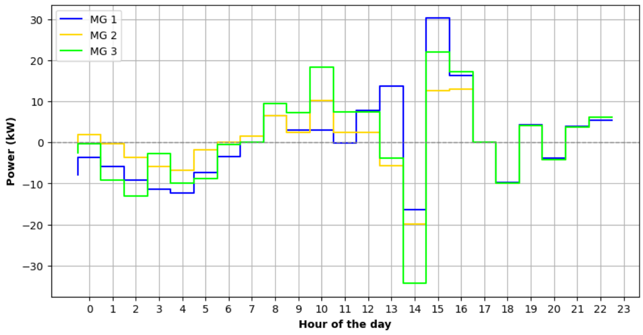

Fig. 5. Individual microgrid's BES day-ahead operation profile

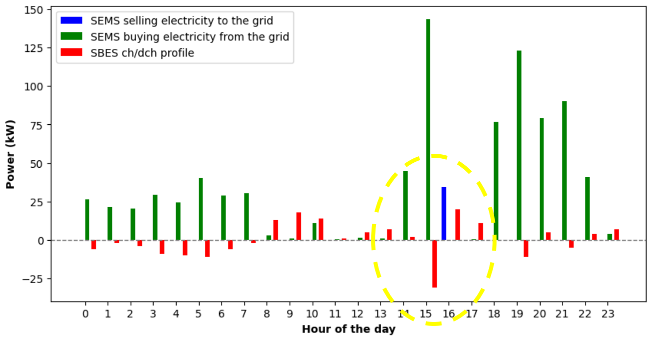

Fig. 6. Optimized energy scheduling profile of the cluster

When considering SBES, a different analysis approach is required. The main scenario for higher-level energy management entails initial SoC = 10, SBES capacity = 60, and load demand flexibility = [5%, 5%, 10%]. Under these conditions, the SBES operating state experiences 10 changes, incurring an associated cost of $1.84. The percentage of cost attributed to CiOS stands at 0.602%. Consequently, the total operational cost of SBES amounts to $5.924, contributing to the C-EMS total operational cost of $305.893. Moreover, the total system operational cost, encompassing exchanges and microgrid internal costs, totals $1007.511. The aggregate total cost of microgrids operating individually is $1037.823. Given this value with the current SBES configuration, the overall cost reduction for the entire system amounts to $30.312, representing a 2.921% reduction. Fig. 6 illustrates the performance of C-EMS in determining whether to buy or sell electricity or to charge or discharge the SBES. At hour 15, the optimal decision is to purchase electricity from the main grid while simultaneously charging the SBES. This stored energy, combined with local generation, sufficiently meets the load demand at hour 16, enabling surplus energy to be sold to the grid for profit, given the higher price at that timeslot. Fig. 7 illustrates the operating state and SoC of the SBES, showcasing a pattern where the battery undergoes charging during initial intervals to meet later demands, reaching a fully discharging state by hour 15. Subsequently, the SBES is charged to meet the total required power in subsequent time intervals.

In addition to variables like demand and price, various constants and coefficients of components also impact the optimal solution derived by C-EMS. These include the capacity, initial state of charge (SoC), and cost coefficients of the SBES. Consequently, Table (2) presents the sensitivity analysis of the optimal solution, encompassing the total system cost and the costs related to SBES operation concerning the SBES initial SoC and its installed capacity. In this table, the SBES capacity ranges from 20 to 80 kWh, while the initial state of charge (SoC) varies from 0 to 50 kW. These variations are used to compute other dependent variables. As shown, depending on these values, the total cost reduction ranges from 2.15% at the minimum to 4.43% at the maximum.

VI. Conclusion

The proposed model aims to optimize the operational costs of the microgrid cluster by leveraging an embedded energy storage system, with each microgrid being cooperative and responsible for payments based on its transactions with neighbouring microgrids or the SBES. The mathematical formulation developed for microgrid components, particularly the accurate representation of the SBES, considers various factors such as charging/discharging costs, costs associated with cycling, and lifespan costs. This approach offers the advantage that if the operator chooses net-zero decisions, they can eliminate purchasing electricity from the main grid and instead compensate consumers for load shedding, enhancing consumer satisfaction and boosting social welfare. Additionally, this strategy aids in reducing emissions linked with fossil-based generation from the main grid. By taking into account operational costs, emissions, and social welfare in unison, this decision moves towards sustainability, aligning with SDG 7. Additionally, the proposed methodology aims to minimize the risk of load shedding by providing reserves to all individual microgrids while ensuring system affordability. While the paper does not delve into the settlement of profits among entities within the cluster, various strategies, including a straightforward division of profits based on each entity's investment in the SBES, can be considered in the future.

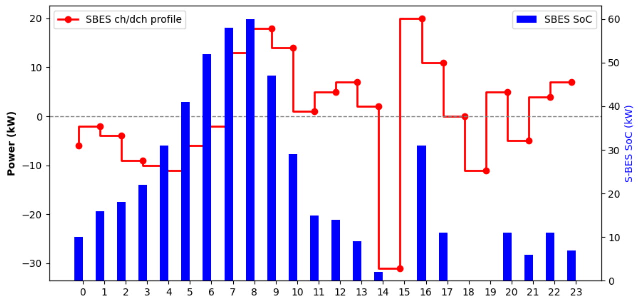

Fig. 7. Optimized SBES ch/dch profile and SoC

TABLE 2. The sensitivity of the cluster's total operational cost to SBES capacity and initial SoC

No. of Exp.	S-BES Capacity	Initial SoC(kW)	Number of CiOS	The cost associated with CiOS (%)	The total cost of S-BES operation ($)	The total operational cost ($)	Total cost reduction (%)
1	80	50	13	0.8	6.55	991.75	4.43
2	80	10	10	0.6	6.36	1006.44	3.02
3	80	0	10	0.6	6.55	1010.35	2.64
4	60	50	14	0.8	6.28	993.01	4.3
5	60	10	10	0.6	5.92	1007.51	2.9
6	60	0	10	0.6	6.03	1011.37	2.54
7	40	40	15	0.9	5.76	998.52	3.78
8	40	10	14	0.9	5.92	1009.77	2.70
9	40	0	14	0.7	5.49	1013.12	2.38
10	20	20	14	0.7	4.34	1007.72	2.9
11	20	10	14	0.9	4.56	1011.67	2.52
12	20	0	14	0.8	4.59	1015.42	2.15

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